4-2017

Infrastructure Development, Income Inequality and Urban Sustainability in the People's Republic of China

Octasiano Miguel Valerio Mendoza
Nagoya University

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This paper examines the relationship between infrastructure development and income inequality in urban People's Republic of China. Recent policies target reductions in income inequality while increasing sustainable urban development. Infrastructure investment plays a key role in achieving both goals, yet the effects of different infrastructures on income disparities at the city level remain undetermined. Using 10 city-level infrastructure indicators relating to sustainable urban development and city income inequality measures, calculated using the China Household Income Project (CHIP) Surveys, this study investigates the correlation between infrastructure and inequality from 2005 to 2013. The results indicate that wastewater treatment, domestic waste management, public green spaces, water efficiency, and residential power efficiency infrastructures were negatively correlated with income inequality with a lag of 2 or 3 years. Investment in these infrastructures might be associated with reductions in inequality ranging from 4% to 49%. Conversely, mass transit usage was positively correlated with income inequality both 2 and 3 years later. An increase in mass transit ridership of 20 trips per capita annually might be associated with a 1% rise in income inequality after 2 years. Increase in water supply coverage and Internet access were also positively correlated with rising inequality. Investment in these infrastructures might warrant further measures to ensure adequate distributional outcomes.

Keywords

income inequality, infrastructure, PRC, sustainable urban development

Comments

Suggested Citation

Valerio Mendoza, O. M. (2017). *Infrastructure development, income inequality and urban sustainability in the People's Republic of China* (ADBI Working Paper No. 713). Tokyo: Asian Development Bank Institute.

ADBI Working Paper Series

INFRASTRUCTURE DEVELOPMENT, INCOME INEQUALITY AND URBAN SUSTAINABILITY IN THE PEOPLE'S REPUBLIC OF CHINA

Octasiano Miguel Valerio Mendoza

No. 713
April 2017

Asian Development Bank Institute

Octasiano Miguel Valerio Mendoza is PhD candidate at the Graduate School of International Development of Nagoya University, Nagoya, Japan.

Suggested citation:

Valerio Mendoza, O. M. 2017. Infrastructure Development, Income Inequality and Urban Sustainability in the People's Republic of China. ADBI Working Paper 713. Tokyo: Asian Development Bank Institute. Available: https://www.adb.org/publications/infrastructure-development-income-inequality-and-urban-sustainability-prc

Please contact the authors for information about this paper.

Email: octasiano.miguel.valerio@f.mbox.nagoya-u.ac.jp

Asian Development Bank Institute
Kasumigaseki Building, 8th Floor
3-2-5 Kasumigaseki, Chiyoda-ku
Tokyo 100-6008, Japan

Tel: +81-3-3593-5500
Fax: +81-3-3593-5571
URL: www.adbi.org
E-mail: info@adbi.org

Abstract

This paper examines the relationship between infrastructure development and income inequality in urban People's Republic of China. Recent policies target reductions in income inequality while increasing sustainable urban development. Infrastructure investment plays a key role in achieving both goals, yet the effects of different infrastructures on income disparities at the city level remain undetermined. Using 10 city-level infrastructure indicators relating to sustainable urban development and city income inequality measures, calculated using the China Household Income Project (CHIP) Surveys, this study investigates the correlation between infrastructure and inequality from 2005 to 2013. The results indicate that wastewater treatment, domestic waste management, public green spaces, water efficiency, and residential power efficiency infrastructures were negatively correlated with income inequality with a lag of 2 or 3 years. Investment in these infrastructures might be associated with reductions in inequality ranging from 4% to 49%. Conversely, mass transit usage was positively correlated with income inequality both 2 and 3 years later. An increase in mass transit ridership of 20 trips per capita annually might be associated with a 1% rise in income inequality after 2 years. Increase in water supply coverage and Internet access were also positively correlated with rising inequality. Investment in these infrastructures might warrant further measures to ensure adequate distributional outcomes.

Keywords: income inequality, infrastructure, PRC, sustainable urban development

JEL Classification: C33, H54, O18, D63, H30, R11

Contents

1. INTRODUCTION

The staggering economic growth of the People's Republic of China (PRC) over the last three and a half decades has seen its economy undergo several reforms as it transformed into the second largest economy in the world, while lifting millions out of poverty, and experiencing breakneck urbanization. Amidst this unbridled growth, however, issues regarding inequality and sustainability have transpired. Against the backdrop of the latest phase of its economic transition, underscored by the "new normal" growth rates and "supply-side reforms," investment in infrastructure will be a key factor in the transition towards a consumer-driven economy that focuses on sustainable development. As social sustainability replaces gross domestic product (GDP) as the target of new growth, local governments will strive to prosper within the neoteric environment defined by improved welfare. Urban infrastructure remains a component in driving economic growth, however, managing and prioritizing investment in different types of infrastructure while achieving social targets could prove challenging if the relationship between these infrastructures and social wellbeing are unknown.

The aim of this paper is to uncover associations between infrastructure and income inequality in urban PRC. Plenty of studies have analyzed the effects of infrastructure and growth, including some with allusions to inequality, however, most are done at the regional or provincial levels and focus on a couple of indicators, such as telephone usage, highways, or railways. Using ten infrastructure indicators, associated with the China Urban Sustainability Index[1], and measuring income inequality for several cities, this study evaluates the

correlation between income inequality and infrastructure at the city level. The focus of this study is not to establish causality, but to highlight which infrastructure indicators are positively or negatively correlated with changes in inequality. Urban social sustainability efforts can be benefited by insights provided by identifying these relationships.

The remainder of this paper proceeds as follows: the next section provides a brief summary of income inequality in the PRC. Section Three describes Infrastructure Development in Urban PRC. In Section Four, the methodology and data are explained. Section Five reports the empirical results from the different models. In Section Six, policy implications are explored. Section Seven provides the concluding remarks.

2. INCOME INEQUALITY IN THE PRC

The first 2 decades of reform generated unprecedented growth in the PRC. In the second decade, rising income inequality resulting from uneven growth surfaced as a serious threat to the PRC's prosperity. Consequently, reducing regional inequality was placed as a top policy priority in the PRC's Ninth Five Year Plan (1996–2000) (Wei 2002). Widening income gaps between the coastal and inland regions, as well as between urban and rural areas, prompted a policy response to boost the economic development in western provinces, embodied in the Western Development Program launched in 1999 (Fan and Sun 2008). Subsequently, the Eleventh Five Year Plan (2006–2010), stressed inequality reduction as a means to achieve a harmonious

[1] "The China Urban Sustainability Index is an annual research project undertaken by the McKinsey Global Institute (MGI) and the Urban China Initiative (UCI). UCI is a think tank co-founded by McKinsey and Company, Columbia University, and Tsinghua University in 2010." (Xiao, Xue, and Woetzel 2010)

socialist society (NPC 2006). The importance of reducing income inequality has since been an integral part of Chinese development strategy.

There is a massive body of literature on income inequality in the PRC using different indicators, such as income, consumption, and output, and various measures of inequality, such as the coefficient of variance (CV), Gini coefficient, and General Entropy Indexes, among others. It became apparent that different indicators and measurements of inequality revealed different findings (Morduch and Sicular 2002; Wei 2002). Similarly, different studies have identified an assortment of determinants that explain changes to inequality. These include location, infrastructure, domestic and foreign capital investment, decentralization, central fiscal transfers, and degree of openness, among others (Fleisher and Chen 1997; Démurger et al. 2002; Wan 2008; Fan, Kanbur, and Zhang 2010; Li, Sato, and Sicular 2013).

Regional disparities are also evident in terms of sustainability performance, whereby “cities in the east showed the strongest level of overall sustainability, followed by cities in central and western China” (Li, Li, Woetzel, Zhang, and Zhang 2014, p.1). The importance of developing infrastructure was clearly stated in the Development of the Western Region Strategy in 2000 (State Council 2000). Improving infrastructure to overcome regional inequality is essential; however, the development strategies for the interior provinces should be different from that of the coastal regions (Démurger et al. 2002; Valerio Mendoza 2014). Henceforth, efforts to reduce inequality appear to be intertwined with investment in infrastructure.

Numerous studies have observed that investment in infrastructure in the PRC has a positive impact on growth and productivity, and can contribute to the reduction of regional income inequalities (Fleisher and Chen 1997; Démurger 2001; Démurger et al. 2002; Xiaolu 2006; Fleisher, Li, and Zhao 2010). However, most studies focus on a few indicators, such as the percentage of urban telephone subscribers and length of roads per square kilometers, as proxies for telecommunication and transportation infrastructures respectively.[2] Although it is generally agreed that the provision of public infrastructure, including telecommunication and transportation facilities, could increase employment opportunities, thus reducing income inequality (Xiaolu 2006). Previous studies have drawn attention to a link between infrastructure development and inequality, despite being limited by a narrow range of infrastructure indicators. There is still a considerable research gap pertaining to a variety of urban infrastructures and their relationships with inequality. This paper contributes to the existing literature on income inequality in the following ways: first, the paper considers a broader range of urban infrastructures, contrary to most studies using one or two indicators, the number of infrastructure indicators and proxies is expanded; additionally, while many studies consider infrastructure as a confounding variable in their growth or poverty equations, this study tries to uncover correlations among several infrastructures as the main explanatory variables.

3. INFRASTRUCTURE DEVELOPMENT IN THE PRC

Infrastructure development has fueled economic growth in the PRC, supporting its export-oriented economy and facilitating the expansion of economic activities in areas that had geographical constraints. Furthermore, basic infrastructure connected raw materials providers to producers, and finally to consumers, reducing

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[2] Lagged variables are used to account for the possibility of delay in their effect.

inefficiencies and competitiveness problems which could hinder economic development (Démurger 2001).

The PRC's investment-led growth has given rise to challenges relating to overcapacity, misallocation of resources, and pollution. Over the past decade, however, the emphasis on sustainable urban development has gained momentum. Over a hundred cities were designated for sustainable development in the Eleventh Five Year Plan (NPC 2006). Additionally, the Twelfth Five-Year Plan marked a change towards higher quality growth, outlining the increase in metro and light-rail construction in urban PRC and a reduction in water consumption per unit of GDP (NPC 2011). This shift towards a more balanced growth continued. Following the Third Plenary Session of the 18th Communist Party of China (CPC) Central Committee in 2013, a new path of urbanization was proposed whereby economic sustainability, social development, and resource preservation supplanted GDP, and growth rates were no longer the main performance indicators (Li, Li, Woetzel, Zhang, and Zhang 2014).

In an effort to measure a city's overall sustainability, the Urban China Initiative (UCI) developed its Urban Sustainability Index (USI) in 2010 (Xiao, Xue, and Woetzel 2010). This Index measures a city's performance in five categories: Basic Needs, Resource Efficiency, Environmental Health, Built Environment, and Commitment to Sustainability.[3] Infrastructure related indicators in the USI include Sewage and Waste Management, Public Transportation, Telecommunication, and Utilities.

The previous section emphasized that research on infrastructure and income inequality was limited by a narrow selection of infrastructure indicators. This study extends the prevailing literature, while also contributing to the current policy targets of investing in superior infrastructure while promoting sustainable development, by using the infrastructure-related indicators and proxies from the USI. The remainder of this section will briefly overview the infrastructure included in the USI, including relevant literature using these indicators, and will conclude with a theoretical framework for how they may affect inequality levels within each city.

3.1 Sewage and Waste Management

Wastewater treatment plants, as well as sewage and drainage structures, have become a necessary part of a modern city's infrastructure, ensuring the quality of drinking water but also protecting against floods and other hazards. As the incomes of urban residents increase, so will their demand for better environmental quality, including but not limited to the quality of water. This increased quality could have a positive effect on the welfare of residents, which can manifest themselves as reduced mortality rates, improved health conditions, and better food safety (Gasparati and Woolf 1985; Zhang 2012; Lam, Remais, Fung, Xu, and Sun 2013).

While many countries have problems with waste disposal, the PRC's rapid urbanization has created growing amounts of household solid waste. Over the first 3 decades of economic reform, municipal solid waste grew by over 7% annually in the PRC (State Statistical Bureau of China 2009), and it became the world's largest producer of waste in 2004. One of the problems the country faces has to do with the method of waste

[3] While there are many urban sustainability frameworks by the World Bank, United Nations, Organisation for Economic Co-operation and Development (OECD), and other institutions, most ignore data constraints found in developing economies. UCI's Urban Sustainability Index uses data that is available particularly in the PRC. Data is compiled from sources including the Chinese City Statistical Yearbooks, individual city yearbooks, State Environmental Protection Administration Yearbooks, and Urban Construction Yearbooks.

treatment. The bulk of waste in the PRC is treated by landfill, followed by incineration, while not much is reused or recycled. Chen, Geng, and Fujita (2009) highlight that while big cities can suffer from landfill overload, waste treatment problems are most serious in second-tier and third-tier cities, where waste piling can contribute to land and water pollution everywhere in a city. Furthermore, Chen (2010) underscores that regional inequalities in income and other socioeconomic characteristics can be conducive to variation in waste generation, recycling, and collection. Households with higher incomes may generate more solid waste as a result of higher consumption. Additionally, this study found an inverted N-shaped curve between income levels and waste disposal.

Although previous studies have identified links between income inequality and sewage and waste treatment, these links have been established at the inter-regional level, and not the city level. This paper further extends and contributes to the literature on sewage and wastewater treatment and their relationship with income distribution by examining these relationships in urban areas.

3.2 Public Transportation

While transportation facilities, such as highways, contribute to the reduction of income inequality (Xiaolu 2006), a city will usually reach a limit in the development of roads, which can lead to congestion if the use of passenger vehicles increases. Metro or light rail systems and public bus services constitute the essence of urban transit infrastructure. These are expected to improve air quality and reduce congestion, emissions, and health costs (OECD 2015a). The rise in urban mass transit usage has been driven by strong improvements in the least developed cities (Xiao, Xue, and Woetzel 2010).

3.3 Information and Communications Technology

During the pre-reform years, investments in telecommunication infrastructure were almost nonexistent, hence at the beginning of the 1980s the PRC was poorly endowed in terms of telecommunication facilities (Démurger 2001). It was not until the 1990s that investment in telecommunication services gradually emerged as a major policy priority. Xiaolu (2006) estimated that telephone coverage had positive and significant effects on income inequality, suggesting that telephone usage was limited to only the middle- and high-income groups in the rural regions. Fleisher, Li, and Zhao (2010) show that investment in telecommunications infrastructure can increase growth and reduce regional inequality if implemented in the less-developed regions. However, they caution that investment in telecommunications infrastructure in developed regions could exacerbate regional disparities. Information and communications technology infrastructure has been a tool in facilitating transactions and reducing time and costs of doing business. Furthermore, OECD (2015b) uncovered in a cross-country analysis that access to the Internet can be conducive to greater income disparities. However, there is no cross-city, within-country analysis exploring this relationship, particularly in the case of the PRC. This paper addresses this research gap.

3.4 Utilities

Since the reform period starting in 1978, the electricity sector in the PRC has developed at similar growth rates to GDP. The installed capacity of electricity generation and the amount of power generated grew at annual growth rates of 9.1% and 9.2%, respectively (Bai and Qian 2010). Urban households have enhanced their welfare through improved access to clean water and power. While differences in energy consumption per capita have been explained mostly by differences in affluence (Duro, Alcántara, and Padilla 2010), a previous study in the PRC suggests that energy efficiency eventually improves with economic growth following a U-shape relation between efficiency and per capita income (Hu and Wang 2006). While most studies on public utilities and their effect on welfare focus on GDP and GDP per capita growth rates, there is still a scarcity of research exploring their association with inequality.

3.5 Public Green Space

There are hundreds of studies postulating the health benefits of public green space (Lee and Maheswaran 2010), through many channels including, but not limited to, the promotion of physical activity and through the absorption of carbon dioxide and emission of oxygen. Green spaces have become a centerpiece in sustainable urban development providing environmental oases within cities, making them more attractive places to live and work in (Xiao, Xue, and Woetzel 2010). The association between public green space coverage and inequality remains undetermined.

3.6 Theory

The aforementioned infrastructures can affect income inequality levels within each city both directly and indirectly. The most obvious direct impact is through the immediate job creation in building these projects. This effect can be captured through input variables, including infrastructure investment figures. This paper, however, focuses on the indirect effects, which are best examined by outcome variables such as coverage and usage data, which are measured after the completion of these projects. The most common indirect effect on inequality is via the improvement in health conditions. It is more likely that those not covered by public utilities and waste treatment facilities are the poorer households at the bottom of the income distribution. By having access to energy, public water, wastewater treatment, and solid waste disposal, these residents might experience a diminished degree of illness and death rates, which in turn would reduce their medical expenditures, thus increasing their disposable income while minimizing income inequality in a city. Additionally, having improved health can enhance productivity, which can also increase incomes and decrease disparities. Public green space is also associated with improved health; however, its access and usage are not as eminent as public utilities and waste treatment.

Another indirect influence may manifest through the improvement of employment conditions and opportunities. Public transportation can reduce commuting times and costs, while increasing the amount of distance traveled, connecting potential employees and employers within a much larger commute radius. Reduced commuting costs can lead to higher disposable incomes, while increased employment opportunities can lead to better jobs. Telecommunications infrastructure can also reduce transaction costs and improve employment opportunities by increasing access to information about jobs and recruitment prospects. Access to information via various online outlets and repositories can also enable autodidactic skills improvement, which can also be conducive to better paid working conditions. All of these beneficial contributions of sustainable infrastructure to income inequality assume that access to these is distributed fairly equally.

4. METHODOLOGY

This paper tests the relationship between income inequality, the dependent variable, and sustainable infrastructure indicators, the independent variables, as shown in the following model:

$$l(y)_{it} = \alpha_i + \beta X_{it-q} + \varepsilon_t \quad (1)$$

where I(y) is income inequality, which is regressed by a vector of coefficients β and explanatory variables X. Subscript i and t represent city and year, respectively. Subscript q indicates the lag time, which in this case will range from 0 to 2.

In order to test this model, data was compiled from several sources into one unique dataset with 209 observations. First, this paper measured inequality of disposable household income per capita (DHIPC) using household surveys. The urban datasets from the China Household Income Project (CHIP)/Rural–Urban Migration in China Project (RUMiC) surveys contain about 5,000 households from around 18 cities for sample years 2007 and 2008.[4] Additionally, the CHIP 2013 urban dataset further expanded the coverage to over 6,000 households from 125 cities.

While the Gini coefficient, Mean Log Deviation (MLD), and Theil indices are the most used in the literature, different indices can reveal qualitatively different results about the disparities being measured. While the Gini and MLD are more susceptible to changes near mean incomes, the Theil index and the generalized entropy index (GE) (2), also known as half the squared coefficient of variation, are more sensitive to changes at the top of the distribution; on the other hand, the Atkinson indexes are more sensitive to changes at the bottom (Atkinson 1970, 1975; De Maio 2007). Therefore, in this study, inequality of DHIPC is measured using all of the aforementioned indices, including epsilon values of 0.5, 1.0, and 2.0 for the Atkinson index. However, given that the Atkinson with an inequality aversion parameter (epsilon) of 2.0 considers income inequalities at the bottom of the distribution, most of the subsequent analyses use this measure.

Furthermore, Sustainable Infrastructure Indicators, outlined in Table 1, were obtained for the 185 cities used in the USI from 2005 to 2011. These indicators were matched with the Cities and Inequality Measures described in Table 2, in order to produce a total of 209 observations, including 1- and 2-year lags for the infrastructure indicators (15 observations for 2005, 17 for 2006–2007, 16 for 2008, and 48 for 2009–2011, for a total of 209 observations to be matched to the dataset of cities in Table 2).

In addition to the infrastructure indicators, the urbanization rate was taken as an imperfect proxy for all kinds of geographical characteristics related to each city's economic structure (Démurger 2001). Urban density is included as previous research indicates it affects other independent variables (Chen 2010; Li, Li, Woetzel, Zhang, and Zhang 2014), however, an insignificant effect on inequality could be due to the opposite impact of its short-run and long-run effects (Xiaolu 2006). In this dataset, however, urban density and income inequality have a linear relationship, therefore nullifying the effects of any inflection points discussed in previous research (Li, Li, Woetzel, Zhang, and Zhang 2014).

[4] For detailed information on sampling design, methodology and implementation of the CHIP/RUMiC surveys see Kong (2010) and Li, Sato, and Sicular (2013).

Table 1: Sustainable Infrastructure Indicators

Infrastructure Components	Indicators
Wastewater Treatment Facilities	Wastewater treatment rate (%)
Solid Waste Treatment Facilities	Domestic waste treated (%)
Mass Transit System	Passengers using mass transit (per capita)
Public Green Space	Coverage area (%)
Information and Communication Technology	Household Internet Access (%)
Energy	Energy consumption (SCE/GDP)
Power Efficiency	Residential power efficiency (kwh per capita)
Water Supply	Public water supply coverage (%)
Water Efficiency	Water efficiency (liters/GDP)

SCE/GDP = standard coal energy per unit of gross domestic product; kwh = kilowatt-hour.

Source: Raw indicators from the Urban Sustainable Index, compiled from Chinese City Statistical Yearbooks, individual city yearbooks, State Environmental Protection Administration Yearbooks, and Urban Construction Yearbooks.

Table 2: Number of Cities and Inequality Measures

Year	Pooled	Panel A	Panel B	Source
2007	15	10	–	CHIP 2007 (RUMiC2008)
2008	17	10	–	CHIP 2008 (RUMiC2009)
2011	48	10	48	CHIP 2013
2012	48	10	48	CHIP 2013
2013	48	10	48	CHIP 2013
Total	176	50	144	

Note: Only cities that matched the indicators in Table 1 are selected from the sources.

Table 3 displays the summary statistics for the inequality measures of DHIPC. The inequality indices are ordered from top to bottom by sensitivity to disparities in different areas of the income distribution. The top value, GE (2), is most sensitive to changes at the top of the distribution, followed by the Theil index, and ending with the Atkinson indices. The Gini coefficient and Atkinson indices have values that range from zero to one; zero representing complete equality, and one complete inequality. The MLD, Theil, and GE (2) indices, on the other hand, have no upper limit; the range for these Generalized Entropy variables is thus higher than the first set of indices. Comparison between the Gini and the Atkinson coefficients reveals that income inequality is much higher for the bottom of the distribution [(2)] than close to the mean.

The descriptive statistics of the explanatory variables are shown in Table 4. The ranges for each variable are wide because they cover a 6-year period. In Table 5, however, the change in mean values from 2005 to 2011 can be seen. While some cities have managed to extend the coverage rates for sewage and solid waste treatment to almost all their residents, the mean coverage rates are still below 90%, indicating that most cities have only a modest improvement to make. The average coverage rate for public green space increased less than 4% from 35.87% in 2005 to 39.42% in 2011. Given that some cities have a coverage area of 69%, there is ample room for continued growth in most cities.

Table 3: Summary of Inequality Measures

Variable	Obs	Mean	Std. Dev.	Min	Max
GE (2)	176	0.2366	0.2446	0.0585	1.9327
Theil	176	0.1681	0.0769	0.0559	0.4979
Gini	176	0.3033	0.0544	0.1876	0.4417
MLD	176	0.1665	0.0649	0.0555	0.3447
A (0.5)	176	0.0791	0.0304	0.0275	0.1805
A (1)	176	0.1516	0.0534	0.0540	0.2916
A (2)	176	0.2891	0.1047	0.1029	0.8659

GE = generalized entropy index; MLD = Mean Log Deviation; A = Atkinson index; Obs = observations; Std. Dev. = standard deviation.

Note: All measures are of disposable household income per capita (DHIPC).

Source: Author’s calculations using the datasets outlined in Table 2.

Internet access has seen modest improvement in most cities. While some cities have achieved complete coverage of their residents, the mean access rate in 2011 remained at less than 50%. Energy consumption per unit of GDP fell from 13.46 in 2005 to 10.32 in 2011, while power efficiency has become more intense, increasing from 0.46 kWh per capita in 2005 to 0.69 kWh per capita in 2011. Whereas water supply coverage has continued to improve, water efficiency dropped from 0.11 liters/GDP in 2005 to 0.10 liters/GDP in 2011.

Table 4: Descriptive Statistics of Explanatory Variables 2005–2011

Variable	Obs	Mean	Std. Dev.	Min	Max
Waste water treatment (%)	209	80.05%	14.73%	31.00%	100.00%
Domestic waste treated (%)	209	89.18%	17.24%	23.00%	100.00%
Mass transit usage (per capita)	209	135.20	66.08	0.34	407.68
Public green space (%)	209	38.99%	6.24%	20.00%	69.00%
Internet access (%)	209	40.36%	21.96%	5.00%	100.00%
Energy consumption (SCE/GDP)	185	11.67	5.55	4.59	32.22
Power efficiency (kwh per capita)	209	0.59	0.29	0.17	1.99
Public water supply (%)	209	96.19%	8.06%	55.00%	100.00%
Water efficiency (liters/GDP)	209	0.10	0.11	0.01	0.89

Obs = observations; Std. Dev. = standard deviation; SCE/GDP = standard coal energy per unit of gross domestic product; kwh = kilowatt-hour.

Notes:

1. For all indicators except Energy Consumption, there are 15 observations for 2005, 17 for 2006–2007, 16 for 2008, and 48 for 2009–2011, for a total of 209 observations to be matched to the 60 cities in Table 2, including 1- and 2-year lags.
2. Residential power efficiency data is missing for Guangzhou in 2008.
3. Energy Consumption data are missing for Baiyin, Fushun, Jinzhou, Kunming, Lanzhou, Qujing, Shenyang, and Tianshui from 2009–2011.

Source: Raw indicators from the Urban Sustainable Index, compiled from Chinese City Statistical Yearbooks, individual city yearbooks, State Environmental Protection Administration Yearbooks, and Urban Construction Yearbooks.

Table 5: Descriptive Statistics of Explanatory Variables 2005 and 2011

	2005			2011		
Variable	**Obs**	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**
Waste water treatment (%)	15	63.73%	16.64%	48	87.04%	10.01%
Domestic waste treated (%)	15	82.47%	18.29%	48	93.13%	13.12%
Mass transit usage (per capita)	15	137.96	41.89	48	138.93	65.56
Public green space (%)	15	35.87%	5.05%	48	39.42%	5.87%
Internet access (%)	15	34.60%	23.37%	48	46.46%	23.40%
Energy consumption (SCE/GDP)	15	13.46	6.37	40	10.32	5.81
Power efficiency (kwh per capita)	15	0.46	0.12	48	0.69	0.36
Public water supply (%)	15	95.60%	6.80%	48	98.35%	3.73%
Water efficiency (liters/GDP)	15	0.11	0.06	48	0.10	0.10

Obs = observations; Std. Dev. = standard deviation; SCE/GDP = standard coal energy per unit of gross domestic product; kwh = kilowatt-hour.

Notes:

1. For all indicators except Energy Consumption, there are 15 observations for 2005, 17 for 2006–2007, 16 for 2008, and 48 for 2009–2011, for a total of 209 observations to be matched to the 60 cities in Table 2, including 1- and 2-year lags.
2. Energy Consumption data are missing for Baiyin, Fushun, Jinzhou, Kunming, Lanzhou, Qujing, Shenyang, and Tianshui in 2011.

Source: Raw indicators from the Urban Sustainable Index, compiled from Chinese City Statistical Yearbooks, individual city yearbooks, State Environmental Protection Administration Yearbooks, and Urban Construction Yearbooks.

5. RESULTS

The results for ordinary least square (OLS) regression estimates are first presented for every inequality measurement, using separate models for no-lag, 1-year lag, and 2-year lagged predictors. The purpose of this exercise is to highlight differences and similarities between the inequality measurements, which is why only the sign of the coefficient and significance level are displayed. Afterwards, OLS, random effects (RE), feasible generalized least squares (FGLS), and fixed effects (FE) estimation results are examined using the Atkinson (A)(2) index for DHICP. These are followed by just-identified instrumental variable regressions (IV) and over-identified two-stage least squares (TSLS) and generalized method of moments estimates (GMM). Lagged variables are tested separately. Post-estimation tests including the Breusch–Pagan Lagrange multiplier (LM) test to test for random-effects, the Breusch–Pagan Test for Heteroscedasticity, the Hausman statistic to test for fixed-effects, and the F-Test for no fixed-effects and "poolability," are presented for each of these tables (Baltagi Econometric Analysis of Panel Data 2013, pp.57–77). Even though one or more of these post-estimation tests will indicate which of the first four models is preferred over the others, presenting the three different estimation techniques is a way to check the robustness of the results. In an effort to deal with endogeneity, post estimation tests for the final three instrumented models are also presented. The Durbin, Wu–Hausman, and C Test statistics are reported in order to ascertain whether the endogenous variables are actually exogenous (Durbin 1954; Wu 1974; Hausman 1978). Weak instruments are tested for using Partial R Squared and Robust F statistics. Finally, over-identification restrictions are tested using Sargan's, Basmann's, and Hansen's J statistic chi-squared tests (Sargan 1958; Basmann 1960; Hansen 1982; Wooldridge 1995).

While we assume that there is a lagged indirect effect between the infrastructure indicators and income inequality, if there is no lag, as displayed in Table 6, we can only interpret any correlations without any direct or indirect effects. The estimates reveal that residential power efficiency is consistently and significantly correlated with income inequality across all measures, indicating that cities with the highest power efficiency are likely to have lower income inequality. Furthermore, domestic waste treated was only significantly correlated with the Gini coefficient, but not the other indices. Moreover, the explanatory power of these infrastructure indicators varies with inequality indices. Depending on the inequality index, the independent variables can explain 13% to 24% of the variation in inequality.

Table 6: OLS Estimates for Disposable Household Income Per Capita (Lag = 0)

Variable	GE(2)	Theil	Gini	MLD	A(0.5)	A(1)	A(2)
Waste water treatment							
Domestic waste treated			(+)*				
Urban density							
Mass transit usage							
Public green space							
Internet access							
Energy consumption							
Residential power efficiency	(–)***	(–)***	(–)***	(–)**	(–)***	(–)***	(–)***
Public water supply							
Water efficiency							
Observations	71	71	71	71	71	71	71
Adjusted R Squared	0.1371	0.2046	0.2421	0.1969	0.2108	0.2025	0.1437

OLS = ordinary least squares; GE = generalized entropy index; MLD = Mean Log Deviation; A = Atkinson index.

Note: *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.

Source: Author's calculation using the CHIP data and raw indicators from the Urban Sustainable Index, compiled from Chinese City Statistical Yearbooks, individual city yearbooks, State Environmental Protection Administration Yearbooks, and Urban Construction Yearbooks.

Table 7: OLS Estimates for Disposable Household Income Per Capita (Lag = 1)

Variable (t-1)	GE(2)	Theil	Gini	MLD	A(0.5)	A(1)	A(2)
Waste water treatment	(–)**	(–)**	(–)**	(–)**	(–)**	(–)**	
Domestic waste treated							
Urban density			(+)*				
Mass transit usage							(+)*
Public green space							
Internet access							
Energy consumption							
Residential power efficiency	(–)*	(–)***	(–)***	(–)***	(–)***	(–)***	(–)***
Public water supply							
Water efficiency	(–)**						
Observations	113	113	113	113	113	113	113
Adjusted R Squared	0.2235	0.1847	0.1814	0.1708	0.1795	0.1739	0.1290

OLS = ordinary least squares; GE = generalized entropy index; MLD = Mean Log Deviation; A = Atkinson index.

Note: *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.

Source: Author's calculation using the CHIP data and raw indicators from the Urban Sustainable Index, compiled from Chinese City Statistical Yearbooks, individual city yearbooks, State Environmental Protection Administration Yearbooks, and Urban Construction Yearbooks.

The estimates using a 1-year lag in independent variables, as seen in Table 7, reveal a slightly less consistent pattern between the different inequality measures. Residential power efficiency remained significantly correlated across all measures. Additionally, six out of seven inequality measures reveal income inequality is significant and negatively correlated with waste water treatment; although it was no longer significant for the A (2), the inequality index most sensitive to the bottom of the distribution. Interestingly, urban density was slightly correlated with the Gini while water efficiency was negatively correlated with the GE (2), the inequality measure sensitive to the top of the distribution. Lastly, for the bottom of the distribution, mass transit usage was positively correlated with inequality at a 10% confidence level. A comparison of the Adjusted R-Squared values confirms that the Atkinson indices explain a lower share of the variation in inequality compared to the other indices, with A (2) having the lowest value, accounting for only 13% of the variation.

Table 8 shows the results of regression estimates using 2-year lagged independent variables. Waste-water treatment is significantly, negatively correlated across all inequality measures at a 1% confidence level, with the exception of the A (2) index, which is only significant at a 5% confidence level. Domestic waste treated is only significantly correlated for the MLD and Atkinson indices, but not the first three inequality measures. Conversely, urban density is only significant at a 10% confidence level for the GE (2) and Theil indices. Similar relationships are evident for public green space. Furthermore, correlations for mass transit and water efficiency were significant for five out of seven indices, while those for residential power efficiency and public water supply were significant for six out of seven indices. All significant correlations display a negative association with inequality, except mass transit usage, which is positively correlated. A comparison of the Adjusted R-Squares reveals that the 2-year-lagged model explains a higher share of the variation compared to the 1-year lag, with the exception of the GE (2) index.

Table 8: OLS Estimates for Disposable Household Income Per Capita (Lag = 2)

Variable (y-2)	GE(2)	Theil	Gini	MLD	A(0.5)	A(1)	A(2)
Waste water treatment	(–)***	(–)***	(–)***	(–)***	(–)***	(–)***	(–)**
Domestic waste treated				(–)**	(–)*	(–)*	(–)**
Urban density	(+)*	(+)*					
Mass transit usage			(+)**	(+)**	(+)*	(+)**	(+)***
Public green space	(–)**	(–)**			(–)*		
Internet access							
Energy consumption							
Residential power efficiency		(–)**	(–)***	(–)***	(–)***	(–)***	(–)***
Public water supply	(–)*	(–)*	(–)*	(–)*	(–)*	(–)*	
Water efficiency		(–)**		(–)**	(–)**	(–)*	(–)*
Observations	151	151	151	151	151	151	151
Adjusted R Squared	0.1618	0.3100	0.2712	0.2851	0.2925	0.2838	0.2432

OLS = ordinary least squares; GE = generalized entropy index; MLD = Mean Log Deviation; A = Atkinson index.

Note: *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.

Source: Author's calculation using the CHIP data and raw indicators from the Urban Sustainable Index, compiled from Chinese City Statistical Yearbooks, individual city yearbooks, State Environmental Protection Administration Yearbooks, and Urban Construction Yearbooks.

The results of the OLS, random-effects, and fixed-effects estimations for inequality of DHIPC using the Atkinson index with a parameter of 2.0 and no lagged independent variables are reported in Table 9. The pooled OLS estimates suggest that cities with higher residential power efficiency are likely also to have lower inequality. None of the post- estimation tests were significant, indicating that the pooled OLS model provides the best estimates, as might be expected with a zero lag time.

Table 9: Estimation Results for DHIPC (Lag = 0)

	OLS	RE	FGLS	FE
Waste water treatment	–0.0399	–0.0399	–0.0233	0.8743*
Domestic waste treated	0.1017	0.1017	0.0369	–0.1844
Urban density	0.0000	0.0000	0.0000	–0.0001***
Mass transit usage	0.0004	0.0004	0.0003***	0.0024
Public green space	0.0346	0.0346	0.1097	0.1049
Internet access	–0.0462	–0.0462	–0.0590	–0.3169
Energy consumption	0.0002	0.0002	0.0006	–0.0106
Residential power efficiency	–0.0988***	–0.0988***	–0.0907***	0.1222
Public water supply	–0.2053	–0.2053	0.0053	–1.2403**
Water efficiency	–0.0482	–0.0482	0.0009	2.2289
Observations	71	71	71	71
Adjusted R Squared	0.0010	0.1437	0.1240	0.4499
LM		0.0000		
Breusch–Pagan			2.6930	
Hausman				12.4821
F Test				20.3145

DHIPC = disposable household income per capita; OLS = ordinary least squares; RE = random effects; FGLS = feasible generalized least squares; FE = fixed effects.

Notes:

1. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.
2. Robust Standard errors using variance–covariance matrix (VCE).
3. FGLS model using homoscedastic panel with no autocorrelation.
4. LM indicates Breusch–Pagan Lagrangian multiplier test for random effects.
5. Hausman and F Test, test for Fixed Effects vs. Random Effects and Pooled OLS, respectively.

Source: Author's calculation using the CHIP data and raw indicators from the Urban Sustainable Index, compiled from Chinese City Statistical Yearbooks, individual city yearbooks, State Environmental Protection Administration Yearbooks, and Urban Construction Yearbooks.

Table 10 conveys the estimation results for inequality using 1-year lagged independent variables. The post-estimation tests indicate that the FE model is preferred over the other models. The results indicate that previous-year-increases in energy consumption are significantly correlated with rising inequality. The coefficients imply that an increase of 1 unit of standard coal energy per unit of GDP (SCE/GDP) was likely to be associated with an increase of 1% in income inequality 1 year later. This model explains over 20% of the variance in inequality. After testing for endogeneity, energy consumption was found to be endogenous in this model. Given the weak instrument in the IV model (Robust F=1.3857) and evidence of homoscedasticity, the estimates in the TSLS model are the most appropriate of the final three. The TSLS model confirms endogeneity with both Durbin and Wu–Hausman tests rejecting exogeneity at a 1% confidence level. The Partial R Squared of 0.5516 and the Robust F statistic of 37.4048, significant at a 1% confidence level, suggest that the instruments used are not weak. Lastly, Sargan's and Basmann's chi-squared tests for over-identifying restrictions are not statistically significant, indicating that the instruments used are valid. After energy consumption was instrumented using its fourth and fifth lags, its association with income inequality 1 year later was reduced to a 0.60% rise from a 1% rise for each additional unit of SCE/GDP. The efficiency of the model was also reduced to explaining only 10% of the variance in inequality.

Table 10: Estimation Results for DHIPC (Lag = 1)

Variable (t-1)	OLS	RE	FGLS	FE	IV	TSLS	GMM
Waste water treatment	–0.1614	–0.1568	–0.1614	0.0370	–0.1764	–0.147	–0.0879
Domestic waste treated	–0.0004	0.0119	–0.0004	0.1594	–0.1118	–0.0287	–0.049
Urban density	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000*	0.0000*
Mass transit usage	0.0004*	0.0004*	0.0004*	–0.0010	0.0003	0.0002	0.0002
Public green space	–0.0119	0.0176	–0.0119	0.1903	0.3913	0.2068	0.1465
Internet access	0.0387	0.0224	0.0387	–0.0592	0.2088	0.1058*	0.0443
Energy consumption	0.0008	0.0009	0.0008	0.0106**	0.0195	0.0060**	0.0033
Residential power efficiency	–0.0835***	–0.0855***	–0.0835**	–0.1819	0.0034	–0.0314	–0.0419***
Public water supply	0.0781	0.0611	0.0781	0.0936	0.3916	0.3384	0.4196
Water efficiency	–0.0493	–0.0588	–0.0493	–0.2931	0.2022	0.1492	0.0693
Observations	113	113	113	113	80	80	80
Adjusted R Squared	0.0436	0.1268	0.1290	0.2059	0.0999	0.0999	0.6327
LM		0.44					
Breusch–Pagan			1.649				
Hausman				15.57*			
F Test				66.61***			
Durbin					3.9867**	14.0530***	
Wu–Hausman					3.5665*	14.4905***	
C Test							5.3416**
Partial R Squared					0.0346	0.5516	0.5516
Robust F					1.3857	37.4048***	37.4048***
Sargan						1.6593	
Basmann						1.4403	
Hansen's J							2.405

DHIPC = disposable household income per capita; OLS = ordinary least squares; RE = random effects; FGLS = feasible generalized least squares; FE = fixed effects; IV = instrumental variable regressions; TSLS = two-stage least squares; GMM = generalized method of moments estimates.

Notes:

1. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.
2. Robust Standard errors using variance–covariance matrix (VCE).
3. FGLS model using homoscedastic panel with no autocorrelation.
4. IV and TSLS refer to just-identified and over-identified 2SLS models, respectively.
5. Energy consumption was instrumented by its fourth lag in the IV model.
6. Energy consumption was instrumented by its fourth and fifth lags in the TSLS and GMM models.
7. LM indicates Breusch–Pagan Lagrangian multiplier test for random effects (Baltagi and Li, A Langrange Multiplier Test for the Error Components Model with Incomplete Panels, 1990).
8. Hausman and F Test, test for Fixed Effects vs. Random Effects and Pooled OLS, respectively.
9. Durbin, Wu–Hausman, and C Test statistics test the exogeneity of endogenous regressors.
10. Partial R Squared and Robust F statistics test for weak instruments.
11. Sargan's, Basmann's and Hansen's J statistic chi-squared tests report over-identifying restrictions.

Source: Author's calculation using the CHIP data and raw indicators from the Urban Sustainable Index, compiled from Chinese City Statistical Yearbooks, individual city yearbooks, State Environmental Protection Administration Yearbooks, and Urban Construction Yearbooks.

Table 11: Estimation Results for DHIPC (Lag = 2)

Variable (t-2)	OLS	RE	FGLS	FE	IV	TSLS	GMM
Waste water treatment	–0.1769**	–0.1803**	–0.1523***	–0.1943*	–0.1231	–0.1249	–0.1309
Domestic waste treated	–0.1130**	–0.1029**	–0.1253***	–0.0579	–0.4377*	–0.4596*	–0.4943*
Urban density	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Mass transit usage	0.0004***	0.0004**	0.0004***	0.0000	0.0004**	0.0004**	0.0005**
Public green space	–0.1942	–0.1991*	–0.1426**	–0.1635	–0.0259	–0.0223	–0.0553
Internet access	0.0161	–0.0497	–0.0088	–0.1009**	0.0203	0.0208	0.0301
Energy consumption	0.0002	–0.0001	–0.0005	0.002	0.0004	0.0004	0.0011
Residential power efficiency	–0.0549***	–0.0421**	–0.0511***	–0.0159	–0.0429**	–0.0424**	–0.0430**
Public water supply	–0.0906	–0.2058**	–0.1766**	–0.2589***	0.6875**	0.7063**	0.7715**
Water efficiency	–0.1106*	–0.2098**	–0.1100***	–0.6749*	–0.1206	–0.1304	–0.146
Observations	151	151	151	151	119	119	119
Adjusted R Squared	0.1891	0.2193	0.2369	0.4999	0.1158	0.1158	0.2797
LM		12.5647***					
Breusch–Pagan			7.3937***				
Hausman				13.6453			
F Test				61.8585***			
Durbin					6.2251**	6.8259***	
Wu–Hausman					8.6942***	9.3161***	
C Test							6.4132**
Partial R Squared					0.0937	0.0951	0.0951
Robust F					3.1213*	2.3865*	2.3865*
Sargan						0.6238	
Basmann						0.5638	
Hansen's J							1.1566

DHIPC = disposable household income per capita; OLS = ordinary least squares; RE = random effects; FGLS = feasible generalized least squares; FE = fixed effects; IV = instrumental variable regressions; TSLS = two-stage least squares; GMM = generalized method of moments estimates; LM = Breusch–Pagan Lagrange multiplier.

Notes:

1. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.
2. Robust Standard errors using variance–covariance matrix (VCE).
3. FGLS model using heteroskedastic panel with no autocorrelation.
4. IV and TSLS refer to just-identified and over-identified 2SLS models, respectively.
5. Domestic waste treated was instrumented by its third lag in the IV model.
6. Domestic waste treated was instrumented by its third and fourth lags in the TSLS and GMM models.
7. LM indicates Breusch–Pagan Lagrangian multiplier test for random effects (Baltagi and Li, A Langrange Multiplier Test for the Error Components Model with Incomplete Panels, 1990).
8. Hausman and F Test, test for Fixed Effects vs. Random Effects and Pooled OLS, respectively.
9. Durbin, Wu–Hausman, and C Test statistics test the exogeneity of endogenous regressors.
10. Partial R Squared and Robust F statistics test for weak instruments.
11. Sargan's, Basmann's and Hansen's J statistic chi-squared tests report over-identifying restrictions.

Source: Author's calculation using the CHIP data and raw indicators from the Urban Sustainable Index, compiled from Chinese City Statistical Yearbooks, individual city yearbooks, State Environmental Protection Administration Yearbooks, and Urban Construction Yearbooks.

The estimation results for inequality of DHIPC using 2-year lagged independent variables are reported in Table 11. The post-estimation tests indicate that FGLS is the preferred model. In this model, the 2-year lagged mass transit usage was positively correlated with income inequality at a 1% confidence level. The results suggest that an increase of 25 trips per capita annually might be associated with a rise in income inequality by 1% 2 years later. Double-lagged wastewater treatment and domestic waste treatment were negatively correlated with income inequality at 1% confidence levels; 1% increases in wastewater and domestic waste treatment are highly likely to be associated with reductions in inequality of 15% and 12% respectively, 2 years later. Two-year-lagged public green space and public water supply were negatively correlated with income inequality at 5% confidence levels. An increase in public green space and public water supply of 1% each is likely to be associated with a reduction in inequality of 14% and 17%, respectively, 2 years later. Finally, double-lagged residential power and water efficiencies were negatively correlated with income inequality at 1% confidence levels. An increase of one kilowatt hour per capita is highly likely to be associated with a 5% reduction in inequality 2 years later, while an increase of water consumption of one liter per unit of GDP is highly likely to be associated with a an 11% reduction in inequality after 2 years. The Adjusted R Squared reveals that 2-year lagged model accounts for over 20% of the variation in inequality.

Out of the several significant regressors in the 2-year-lagged-FGLS, only domestic waste treated was found to be endogenous (GMM C Test = 6.4132**) and was thus instrumented with its third and fourth lags.[5] All three instrumented models exhibited a low Partial R Squared and a Robust F Statistic, indicating weak instruments. However, Sargan's, Basmann's, and Hansen's J statistic chi-squared tests for over-identification indicate that the instruments used are valid, and therefore the following causal inferences are under the weak instruments assumption. Although the GMM estimates are considered most appropriate given the presence of heteroscedasticity, all three instrumented models exhibit very similar coefficients and only four of the seven regressors remain significant in each of the models. The correlation of a 1% increase in domestic waste treated on inequality 2 years later increased from a 12% reduction to 49%. The magnitude of the association of mass transit and inequality was also increased; in this model an increase of only 20 trips per capita annually was likely to be associated to a 1% increase in inequality 2 years later. While the reduction in inequality related to an increase of one kilowatt hour per capita was slightly reduced to 4%, the relationship between water consumption and inequality was reversed to a positive one, where an increase of one liter per unit of GDP was likely to be associated with a 77% rise in inequality. The 2-year-lagged-GMM model accounted for 27% of the variation in inequality.

Table 12 shows the results of the estimates using 3-year lags. The FGLS model indicates that, four out of the seven indicators from the 2-year-lagged-FGLS remained significant: waste water treatment, domestic waste treated, mass transit usage, and residential power efficiency.[6] The correlation with an increase in 1% each of wastewater and domestic waste treatment was of a decrease in inequality 3 years later of 26% and six%, respectively. Similarly, an increase in one kilowatt hour per capita was highly correlated with a 6% reduction in inequality 3 years later, while an increase of mass transit ridership of 20 trips per capita annually was highly likely to be associated with a 1% rise in inequality after 3 years. Additionally, the FGLS revealed inequality was also significantly, positively correlated with increase in Internet access and residential power consumption. However, after instrumentation, the over-justified GMM model corroborates the links with three of the six variables. The GMM model is best suited given the presence of heteroscedasticity, and a higher Robust F and Partial R Squared than the IV model. Hansen's J statistic chi-squared test for

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5 Endogeneity tests for all 2-, 3-, and 4-year lagged regressors are reported in Table A1.

6 The FGLS model is the most appropriate model given that there is heteroscedasticity (Breusch–Pagan = 13.682***), random-effects over OLS (LM = 19.894***), and the Hausman failed to establish Fixed-Effects (Hasman = 15.1487*).

over-identification validate the instruments used, but given the relatively low Robust F of 6.0155***, the following inferences are done under the assumption of weak instruments. In this model, which also accounts for 24% of the variation in inequality, a 1% rise in domestic waste treated was likely to be associated with a reduction in inequality of 32%, 3 years later; a growth in residential power efficiency of one kilowatt hour per capita was slightly related to a 4% fall in inequality after 3 years; and the relationship between mass transit usage and inequality remained unchanged.

Table 12: Estimation Results for DHIPC (Lag = 3)

Variable (t-3)	OLS	RE	FGLS	FE	IV	TSLS	GMM
Waste water treatment	–0.2536***	–0.4093***	–0.2636***	–0.4065**	–0.0872	–0.0863	–0.0782
Domestic waste treated	–0.0688	–0.0365	–0.0673***	0.0029	–0.2713**	–0.3083**	–0.3222**
Urban density	0.0000	0.0000	0.0000	0.0000			
Mass transit usage	0.0005***	0.0005**	0.0005***	0.0002	0.0004***	0.0005***	0.0005***
Public green space	–0.2485*	–0.1544	–0.0907	–0.0902	0.0658	0.086	0.0957
Internet access	0.1102*	0.1085	0.0814***	–0.0241	0.0792	0.0774	0.0717
Energy consumption	0.0016	0.0026	0.0028***	0.0033	0.0014	0.0014	0.0016
Residential power efficiency	–0.0781***	–0.0514*	–0.0683***	–0.0394	–0.0514	–0.0501	–0.0447*
Public water supply	0.1085	0.0159	0.0158	–0.0678	0.2131	0.2235	0.2066
Water efficiency	0.0292	0.0499	0.0241	0.6774*	0.0016	–0.0059	–0.015
Observations	135	135	135	135	119	119	119
Adjusted R Squared	0.1935	0.219	0.241	0.6563	0.0898	0.0898	0.2441
LM		19.8945***					
Breusch–Pagan			13.682***				
Hausman				15.1487*			
F Test				191.442***			
Durbin					4.5023**	6.7499***	
Wu–Hausman					4.2468**	6.4944**	
C Test							8.0904***
Partial R Squared					0.1884	0.205	0.205
Robust F					5.2845**	6.0155***	6.0155***
Sargan						0.9706	
Basmann						0.8881	
Hansen’s J							1.119

DHIPC = disposable household income per capita; OLS = ordinary least squares; RE = random effects; FGLS = feasible generalized least squares; FE = fixed effects; IV = instrumental variable regressions; TSLS = two-stage least squares; GMM = generalized method of moments estimates; LM = Breusch–Pagan Lagrange multiplier.

Notes:

1. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.
2. Robust Standard errors using variance–covariance matrix (VCE).
3. FGLS model using heteroskedastic panel with no autocorrelation.
4. IV and TSLS refer to just-identified and over-identified 2SLS models, respectively.
5. Domestic waste treated was instrumented by thrice-lagged urban density in the IV model.
6. Domestic waste treated was instrumented by its fifth lag and thrice-lagged urban density in the TSLS and GMM models.
7. LM indicates Breusch–Pagan Lagrangian multiplier test for random effects (Baltagi and Li, A Langrange Multiplier Test for the Error Components Model with Incomplete Panels, 1990).
8. Hausman and F Test, test for Fixed Effects vs. Random Effects and Pooled OLS, respectively.
9. Durbin, Wu–Hausman, and C Test statistics test the exogeneity of endogenous regressors.
10. Partial R Squared and Robust F statistics test for weak instruments.
11. Sargan’s, Basmann’s and Hansen’s J statistic chi-squared tests report over-identifying restrictions.

Source: Author’s calculation using the CHIP data and raw indicators from the Urban Sustainable Index, compiled from Chinese City Statistical Yearbooks, individual city yearbooks, State Environmental Protection Administration Yearbooks, and Urban Construction Yearbooks.

Table 13: Estimation Results for DHIPC (Lag = 4)

Variable (t-4)	OLS	RE	FGLS	FE	IV	TSLS	GMM
Waste water treatment	–0.0361	–0.0373	–0.0787***	–0.0031	–0.0427	–0.0427	–0.043
Domestic waste treated	–0.0359	–0.0095	–0.0730***	0.0117	–0.0282	–0.0282	–0.0283
Urban density	0.0000*	0.0000**	0.0000***	0.0000	0.0000*	0.0000*	0.0000*
Mass transit usage	0.0002*	0.0001	0.0003***	–0.0003	0.0003**	0.0003**	0.0003**
Public green space	0.0057	0.0292	0.0073	0.0379	0.0021	0.0021	0.0016
Internet access	0.0617	–0.0822*	0.0544***	–0.1798***	0.1156**	0.1153**	0.1155**
Energy consumption	0.0027	0.0008	0.0019**	–0.0006	0.0029*	0.0029*	0.0029
Residential power efficiency	–0.0501	–0.0542	–0.0505**	–0.0556	–0.0687	–0.0686	–0.0685
Public water supply	0.1199	–0.1302	0.0763	–0.199	0.1204	0.1204	0.1206
Water efficiency	0.0822	–0.0191	0.0660**	0.0559	0.1116	0.1114	0.1114**
Observations	121	121	121	121	121	121	121
Adjusted R Squared	0.0625	0.0346	0.1294	0.82	0.0855	0.0855	0.8884
LM		58.9732***					
Breusch–Pagan			0.0357				
Hausman				14.5902			
F Test				271.3922***			
Durbin					5.6709**	6.336**	
Wu–Hausman					5.3596**	6.023**	
C Test							5.2345**
Partial R Squared					0.8264	0.8432	0.8432
Robust F					216.4889***	117.9888***	117.9888***
Sargan						0.0015	
Basmann						0.0014	
Hansen’s J							0.0017

DHIPC = disposable household income per capita; OLS = ordinary least squares; RE = random effects; FGLS = feasible generalized least squares; FE = fixed effects; IV = instrumental variable regressions; TSLS = two-stage least squares; GMM = generalized method of moments estimates; LM = Breusch–Pagan Lagrange multiplier.

Note:

1. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.
2. Robust Standard errors using variance–covariance matrix (VCE).
3. FGLS model using homoscedastic panel with no autocorrelation.
4. IV and TSLS refer to just-identified and over-identified 2SLS models, respectively.
5. Internet access was instrumented by its fifth lag in the IV model.
6. Internet Acess was instrumented by its fifth and sixth lags in the TSLS and GMM models.
7. LM indicates Breusch–Pagan Lagrangian multiplier test for random effects (Baltagi and Li, A Langrange Multiplier Test for the Error Components Model with Incomplete Panels, 1990).
8. Hausman and F Test, test for Fixed Effects vs. Random Effects and Pooled OLS, respectively.
9. Durbin, Wu–Hausman, and C Test statistics test the exogeneity of endogenous regressors.
10. Partial R Squared and Robust F statistics test for weak instruments.
11. Sargan’s, Basmann’s and Hansen’s J statistic chi-squared tests report over-identifying restrictions.

Source: Author’s calculation using the CHIP data and raw indicators from the Urban Sustainable Index, compiled from Chinese City Statistical Yearbooks, individual city yearbooks, State Environmental Protection Administration Yearbooks, and Urban Construction Yearbooks.

The results of the estimates using 4-year lags are reported in Table 13. The post-estimation tests indicate that the RE model was the most appropriate. Out of all the significant indicators in the previous tables, only Internet access was significantly correlated with inequality after 4 years. While it is negatively correlated at a 10%

confidence level in the RE model, after being instrumented with its fifth lag in the IV model, it became positively correlated at a 5% confidence level. While the IV model's higher Robust F score and the presence of homoscedasticity seem to suggest it is a better fit than the other instrumented models, the difference between the just-identified and over-identified models is minute in terms of the magnitude of coefficients. Furthermore, all three instrumented models exhibit a high Partial R Squared and Robust F statistic, indicating very strong instruments. Furthermore, Sargan's, Basmann's, and Hansen's J statistics chi-squared tests for over- identification confirm that the instruments are valid. In the IV model, 1% increase in Internet access was likely to be linked to an 11% rise in inequality 4 years later. The estimates using 5-year lags are reported in Table 14 and reveal that none of the significant indicators from the 4-year-lagged models remained significantly correlated.

Table 14: Estimation Results for DHIPC (Lag = 5)

Variable (t-5)	OLS	RE	FGLS	FE
Waste water treatment	–0.0156	–0.0183	–0.0454**	–0.0115
Domestic waste treated	–0.0746**	–0.0812**	–0.0843***	–0.0784*
Urban density	0.0000**	0.0000*	0.0000***	0.0000
Mass transit usage	0.0003**	0.0000	0.0003***	–0.0005**
Public green space	0.0300	0.0455	0.0385	0.0541
Internet access	0.0690	0.0324	0.0799***	0.0149
Energy consumption	0.0023	0.0007	0.0013*	–0.0001
Residential power efficiency	–0.0575	–0.0432	–0.0846**	–0.0922
Public water supply	0.0552	–0.0459	–0.0105	–0.0457
Water efficiency	0.0548	–0.0076	0.0612**	–0.0235
Observations	124	124	124	124
Adjusted R Squared	0.096	0.1021	0.1556	0.8304
LM		69.1894***		
Breusch–Pagan			0.6583	
Hausman				9.2405
F Test				195.7985***

DHIPC = disposable household income per capita; OLS = ordinary least squares; RE = random effects; FGLS = feasible generalized least squares; FE = fixed effects; LM = Breusch–Pagan Lagrange multiplier.

Notes:

1. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.
2. Robust Standard errors using variance–covariance matrix (VCE).
3. FGLS model using homoskedastic panel with no autocorrelation.
4. LM indicates Breusch–Pagan Lagrangian multiplier test for random effects
5. Hausman and F Test, test for Fixed Effects vs. Random Effects and Pooled OLS, respectively.

Source: Author's calculation using the CHIP data and raw indicators from the Urban Sustainable Index, compiled from Chinese City Statistical Yearbooks, individual city yearbooks, State Environmental Protection Administration Yearbooks, and Urban Construction Yearbooks.

6. DISCUSSION AND POLICY IMPLICATIONS

The results of the previous section investigated the relationship between income inequality and different sustainable infrastructure indicators. This section analyzes those results by interpreting the reasons and context of possible policy implications. The contributions of these results to the current literature are also presented.

6.1 Sewage and Waste Management

While previous studies have identified inter-regional relationships between sewage and waste management and income disparities, the results from this study identify a negative correlation at the city level. Increases in both wastewater and domestic waste treatment were significantly correlated with reductions in inequality after 2 and 3 years at a confidence level of 1%. Furthermore, in the National Urbanization Plan 2014–2020, sewage treatment and waste disposal rates in urban areas will increase to 95% (State Council 2014). It was expected that increasing wastewater treatment could improve the welfare of residents, especially regarding health, which could in turn improve disposable income, through reduced medical expenses, leading to demand for higher water quality, resulting in further water treatment facilities. Investment in new treatment plants is expected to meet the PRC's new standards for drinking water (Qu, Zheng, Wang, and Wang 2012).

Even though this paper identified sewage and waste treatment infrastructures were associated with reductions in income inequality, these results complement the following considerations raised by other research. As urban sewage and waste treatment rates near full coverage in the following decades, their redistributive effect, mainly reduction in health expenditures, will have a diminishing effect. Therefore, other measures should also be considered to ensure a sustainable effect on welfare. The new water pricing schemes, including progressive tariffs on water use included in the "Water Pollution Prevention and Control Action Plan," also known as the "Water Ten Plan" (State Council 2015), and the increase in treatment fees scheduled for 2016 (NDRC 2015) might be effective in reducing water usage as urbanization and incomes per capita increase. Progressive tariff schemes are intended to penalize water-intensive consumers and to decelerate the rate of water usage in spite of rising urbanization. Wang, Xie, and Li (2010) further demonstrated that a substantial rise in water price is economically feasible as long as the poorest households are properly subsidized.

Growing disposable incomes can raise consumption, thus generating solid waste; but they can also lead to boosting the recycling rate through raising education levels (Chen 2010). Similarly, Wu, Zhang, Xu, and Che (2015) explain that out of the three charging methods implemented throughout the country, a fixed disposal fee, a potable water-based disposal fee, and a plastic bag-based disposal fee, the plastic bag-based disposal fee appeared to be performing well in reducing waste generation.

Even as sewage and waste management treatment rates near full coverage, progressive tariff schemes could shift the burden on higher-intensity, and supposedly higher-income consumers and industries while reducing that of lower-intensity and lower-income households. This redistributive policy could increase the disposable income of poorer households, possibly reducing inequality of DHICP. Finally, the treatment method is also important—while the majority of disposal methods are through landfills and incineration plants, an increase in recycling and compost infrastructure may benefit overall urban welfare. Education policies are also crucial in fomenting environmentally friendly behavior like recycling and green consumption. Increased environmental awareness can incentivize residents to sign up for costlier programs (Kotchen and Moore 2007).

6.2 Public Transportation

The results from this study contradict previous studies, which found that transportation infrastructure, such as highways, contributed to the reduction of income inequality. Increases in mass transit usage were significantly correlated with rising income inequality 2 and 3 years later. It is expected that increasing or optimizing public transportation networks will not only reduce congestion but can improve access to employment opportunities and facilitate the commute of many workers who have to drive or walk long distances. Increasing mass transit use can be attained by lowering bus and subway fares and also by imposing high parking rates for passenger vehicles. Integrated construction around stations and bus stops can also entice residents to use public transportation.

The PRC's most developed urban rail systems, such as those of Beijing and Shanghai, had 26 and 17 kilometers of rail per million people, respectively, as of 2012. While these figures might dwarf other PRC urban areas, they still lag behind cities like London and Tokyo, which have 192 and 69 kilometers of rail per million people, respectively (OECD 2013). There is a vast opportunity for increasing urban rail systems in every city in the PRC. According to the Thirteenth Five-Year Plan (2016–2020), an increasing number of urban railways will be built and around 3,000 kilometers of new urban rail lines will start operation (NPC 2016). Additionally, urban rail systems in 35 cities are projected to be extended by over 6,000 kilometers by 2030 (OECD 2013). These expansions and optimizations[7] of urban transportation systems may lead to slight increases in income inequality in the short term, but their long-term benefits are both assumed and expected.

6.3 Utilities

While energy consumption was positively correlated with rising inequality after 1 year, residential power efficiency was found to be significantly correlated with decreased income inequality after 2 and 3 years. There have been several policies aimed at improving power efficiency, which include the continuous updating and enforcement of building codes, such as "The Code for Acceptance of Energy Efficient Building Construction (GB50411-2007)" and the "Standard for Energy Efficiency Test of Residential Buildings (JGJ/T 132-2009)." Additionally, in 2013 the Ministry of Housing and Urban–Rural Development (MOHURD) revealed the "Green Building Action Plan," which demands the rigorous execution of urban energy codes and retrofitting residential buildings across the country (MOHURD 2013). Other initiatives include the "The Three Star Rating System," which incentivizes "green buildings" by rewarding Two-Star buildings with 45 yuan per square meter and Three-Star buildings with 80 yuan per square meter (MOF 2012). Continued gains in power efficiency will likely lead to reduced income inequality in urban PRC.

Increases in water supply were significantly correlated with rising inequality, while water efficiency was significantly correlated with reductions in inequality, both after 2 years. The "Water Ten Plan" stipulates that water quality will increase over the next 15 years. By 2020, 93% of urban potable water should be of Grade Three or higher. The target will increase to 95% by 2030. Additionally, the increase in water fees,

[7] Démurger (2001) points out that density measures provide only quantitative information on transportation and do not reveal anything about quality, e.g., accessibility and conditions. She suggests investing in network expansion of transport-poor provinces can prove to be very useful for economic growth; however, the best strategy for transport-rich provinces is to invest in upgrading or quality-improvement of existing facilities.

expected in 2016, might be effective in reducing water usage as urbanization and incomes per capita increase. Providing water fee subsidies, or rebates, for low-income households and progressively increasing the fees for higher-income households might help balance the inequities that result in the uneven distribution of the public water supply.

This study identifies links between public utilities infrastructure and income inequality at the city level. Interestingly, the choice of indicator for each type of infrastructure reveals opposing trends. While coverage rate proxies reveal a positive relationship with inequality, efficiency indicators demonstrate a negative relationship. It could, therefore, be argued that improving the efficiency, or quality, of the public utilities infrastructure is of higher importance than merely increasing the supply.

6.4 Public Green Spaces

Increases in public green space were significantly correlated with reductions in inequality after 2 years. By the end of 2016, fourteen first- and second-tier cities are expected to establish and enforce green belts of "permanent farmland" around each city which will remain unoccupied once the land is chosen (Ministry of Land and Resources 2015). Increasing public green spaces is expected to contribute to reduction in pollution and better health of the urban residents. It may also lead to lower income disparities.

While numerous benefits of increasing public green spaces have been outlined in the prevailing literature, this study further extends the list of possible benefits to include improved income equality.

6.5 Information and Communication Technology

The effects of telecommunication infrastructure on income inequality have been shown to be varied in previous studies. The results of this study, however, suggest increases in Internet usage are significantly correlated with rising inequality between 3 and 4 years later. These results might be explained by unequal access to the Internet across the income distribution, where poorer households have less access than those of middle and high incomes. Having access to the Internet and being able to derive income from such access are separate matters, however. Some Internet subscribers may choose to use their online access for educational or entertainment purposes while others may generate income from the creation of content or through e-commerce. These findings are consistent with those of OECD (2015b), which found students of higher socioeconomic backgrounds were able to use their Internet access differently from those of poorer backgrounds. The results from this study suggest that this may also be the case in urban PRC.

The Thirteenth Five-Year Plan stipulates substantial investment in Internet infrastructures aimed at realizing full coverage in urban areas at high speeds provided via fiber-optic networks (NPC 2016). However, increasing Internet access alone might not prove enough to ameliorate disparities. Policies aimed at promoting and integrating Internet access, entrepreneurship, and education may be necessary. Yang et al. (2013) suggest Internet access in urban elementary schools may have serious implications for future education and employment opportunities. Knowledge of how to use the Internet for the betterment of livelihoods may be just as important, or even more important, than the infrastructure itself.

7. CONCLUDING REMARKS

This paper investigates correlations between infrastructure and income inequality in urban PRC. The scope of this study was to establish which infrastructure indicators were positively or negatively correlated with changes in inequality at the city level. The paper used infrastructure indicators relating to urban sustainable development and income inequality measures calculated using household survey data. The results revealed that infrastructure relating to wastewater treatment facilities, domestic waste treatment facilities, public green spaces, residential power efficiency, and water efficiency were negatively correlated with income inequality 2 or 3 years later. While energy consumption was positively associated with rising inequality 1 year later, mass transit usage was positively correlated both 2 and 3 years later; water supply coverage was positively correlated 2 years later, and Internet access showed a positive relationship with income inequality after 3 and 4 years.

Understanding these relationships can be useful in understanding the effects the underlying dynamics and mechanisms of these infrastructures may have on disposable household incomes. The negatively correlated indicators suggest that investment in infrastructure could lead to a more sustainable urban development. The positively correlated indicators require careful examination in ensuring equitable access and distribution. Further research examining these phenomena is needed.

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APPENDIX

Table A1: Endogeneity Tests

Variable	Durbin t-2	Wu t-2	Robust F t-2
Waste water treatment	0.0464	0.0427	33.1086***
Domestic waste treated	5.1476**	4.8377**	3.1213*
Urban Density	0.5120	0.4624	30.0355***
Mass transit usage	0.0697	0.0627	153.3033***
Public green space	0.4076	0.3678	8.5847***
Internet access	2.5883	2.3791	27.3655***
Energy consumption	2.8073	2.5852	4.6355**
Residential power efficiency	0.6466	0.5840	11.0009***
Public water supply	0.6833	0.6179	5.4670**
Water efficiency	4.5322	3.5779	45.9068***
Variable	**Durbin t-3**	**Wu t-3**	**Robust F t-3**
Waste water treatment	0.3605	0.3251	134.9330***
Domestic waste treated	4.7435**	4.4422**	5.0887**
Urban Density	0.0208	0.0187	43.5551***
Mass transit usage	0.5845	0.4994	136.6001***
Public green space	0.5102	0.4355	18.6785***
Internet access	0.7111	0.6433	76.0430***
Energy consumption	2.6896	2.4725	37.4060***
Residential power efficiency	0.6217	0.5414	32.6700***
Public water supply	1.7449	1.5923	11.1203***
Water efficiency	2.3638	2.0666	11.9864***
Variable	**Durbin t-4**	**Wu t-4**	**Robust F t-4**
Waste water treatment	0.0016	0.0014	95.7201***
Domestic waste treated	0.0043	0.0038	0.0164
Urban Density	0.0556	0.0501	31.1615***
Mass transit usage	0.2348	0.2119	241.8920***
Public green space	1.2031	1.0947	3.3165*
Internet access	5.6709**	5.3596**	216.4889***
Energy consumption	0.0341	0.0325	84.1311***
Residential power efficiency	0.0837	0.0755	12.7479***
Public water supply	0.0757	0.0683	5.7906***
Water efficiency	0.1460	0.1316	14.3214***

Notes:

1. *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.
2. All variables tested instrumented using first, second, third, fourth, and fifth lags as well as lagged government spending, household disposable income per capita, urban density, and employment share.
3. Only best results using the different individual and combination of instruments are reported.
4. Durbin and Wu (–Hausman) statistics test the exogeneity of endogenous regressors.
5. Robust F statistics test for weak instruments.

Source: Author's calculation using the CHIP data and raw indicators from the Urban Sustainable Index, compiled from Chinese City Statistical Yearbooks, individual city yearbooks, State Environmental Protection Administration Yearbooks, and Urban Construction Yearbooks.